A Numerical Example (continued)

Cash flows at year 3

<table>
<thead>
<tr>
<th>Path</th>
<th>Year 0</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>2.5476</td>
</tr>
<tr>
<td>3</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0.4685</td>
</tr>
<tr>
<td>6</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>5.6212</td>
</tr>
<tr>
<td>7</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>4.0775</td>
</tr>
<tr>
<td>8</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0</td>
</tr>
</tbody>
</table>
A Numerical Example (continued)

- The cash flows at year 3 are the exercise value if the put is in the money.

- Only 4 paths are in the money: 2, 5, 6, 7.

- Some of the cash flows may not occur if the put is exercised earlier, which we will find out step by step.

- Incidentally, the *European* counterpart has a value of

$$0.951229^3 \times \frac{2.5476 + 0.4685 + 5.6212 + 4.0775}{8} = 1.3680.$$
A Numerical Example (continued)

• We move on to year 2.

• For each state that is in the money at year 2, we must decide whether to exercise it.

• There are 6 paths for which the put is in the money: 1, 3, 4, 5, 6, 7 (p. 895).

• Only in-the-money paths will be used in the regression because they are where early exercise is relevant.
  – If there were none, we would move on to year 1.
A Numerical Example (continued)

• Let $x$ denote the stock prices at year 2 for those 6 paths.

• Let $y$ denote the corresponding discounted future cash flows (at year 3) if the put is not exercised at year 2.
A Numerical Example (continued)

Regression at year 2

<table>
<thead>
<tr>
<th>Path</th>
<th>$x$</th>
<th>$y$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>92.5815</td>
<td>$0 \times 0.951229$</td>
</tr>
<tr>
<td>2</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>3</td>
<td>103.6010</td>
<td>$0 \times 0.951229$</td>
</tr>
<tr>
<td>4</td>
<td>98.7120</td>
<td>$0 \times 0.951229$</td>
</tr>
<tr>
<td>5</td>
<td>101.0564</td>
<td>$0.4685 \times 0.951229$</td>
</tr>
<tr>
<td>6</td>
<td>93.7270</td>
<td>$5.6212 \times 0.951229$</td>
</tr>
<tr>
<td>7</td>
<td>102.4177</td>
<td>$4.0775 \times 0.951229$</td>
</tr>
<tr>
<td>8</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>
A Numerical Example (continued)

- We regress $y$ on 1, $x$, and $x^2$.

- The result is

$$f(x) = 22.08 - 0.313114 \times x + 0.00106918 \times x^2.$$ 

- $f(x)$ estimates the continuation value conditional on the stock price at year 2.

- We next compare the immediate exercise value and the continuation value.\(^a\)

\(^a\)The $f(102.4177)$ entry on the next page was corrected by Mr. Tu, Yung-Szu (B79503054, R83503086) on May 25, 2017.
## A Numerical Example (continued)

**Optimal early exercise decision at year 2**

<table>
<thead>
<tr>
<th>Path</th>
<th>Exercise</th>
<th>Continuation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12.4185</td>
<td>$f(92.5815) = 2.2558$</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1.3990</td>
<td>$f(103.6010) = 1.1168$</td>
</tr>
<tr>
<td>4</td>
<td>6.2880</td>
<td>$f(98.7120) = 1.5901$</td>
</tr>
<tr>
<td>5</td>
<td>3.9436</td>
<td>$f(101.0564) = 1.3568$</td>
</tr>
<tr>
<td>6</td>
<td>11.2730</td>
<td>$f(93.7270) = 2.1253$</td>
</tr>
<tr>
<td>7</td>
<td>2.5823</td>
<td>$f(102.4177) = 1.2266$</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
A Numerical Example (continued)

- Amazingly, the put should be exercised in all 6 paths: 1, 3, 4, 5, 6, 7.
- Now, any positive cash flow at year 3 should be set to zero or overridden for these paths as the put is exercised before year 3 (p. 895).
  - They are paths 5, 6, 7.
- The cash flows on p. 899 become the ones on next slide.
A Numerical Example (continued)

Cash flows at years 2 & 3

<table>
<thead>
<tr>
<th>Path</th>
<th>Year 0</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>—</td>
<td>—</td>
<td>12.4185</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>—</td>
<td>—</td>
<td>0</td>
<td>2.5476</td>
</tr>
<tr>
<td>3</td>
<td>—</td>
<td>—</td>
<td>1.3990</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>—</td>
<td>—</td>
<td>6.2880</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>—</td>
<td>—</td>
<td>3.9436</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>—</td>
<td>—</td>
<td>11.2730</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>—</td>
<td>—</td>
<td>2.5823</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>—</td>
<td>—</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
A Numerical Example (continued)

- We move on to year 1.
- For each state that is in the money at year 1, we must decide whether to exercise it.
- There are 5 paths for which the put is in the money: 1, 2, 4, 6, 8 (p. 895).
- Only in-the-money paths will be used in the regression because they are where early exercise is relevant.
  - If there were none, we would move on to year 0.
A Numerical Example (continued)

- Let $x$ denote the stock prices at year 1 for those 5 paths.
- Let $y$ denote the corresponding discounted future cash flows if the put is not exercised at year 1.
- From p. 907, we have the following table.
A Numerical Example (continued)

Regression at year 1

<table>
<thead>
<tr>
<th>Path</th>
<th>$x$</th>
<th>$y$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>97.6424</td>
<td>$12.4185 \times 0.951229$</td>
</tr>
<tr>
<td>2</td>
<td>101.2103</td>
<td>$2.5476 \times 0.951229^2$</td>
</tr>
<tr>
<td>3</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>4</td>
<td>96.4411</td>
<td>$6.2880 \times 0.951229$</td>
</tr>
<tr>
<td>5</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>6</td>
<td>95.8375</td>
<td>$11.2730 \times 0.951229$</td>
</tr>
<tr>
<td>7</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>8</td>
<td>104.1475</td>
<td>0</td>
</tr>
</tbody>
</table>
A Numerical Example (continued)

• We regress $y$ on $1$, $x$, and $x^2$.

• The result is

$$f(x) = -420.964 + 9.78113 \times x - 0.0551567 \times x^2.$$ 

• $f(x)$ estimates the continuation value conditional on the stock price at year 1.

• We next compare the immediate exercise value and the continuation value.
A Numerical Example (continued)

Optimal early exercise decision at year 1

<table>
<thead>
<tr>
<th>Path</th>
<th>Exercise</th>
<th>Continuation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7.3576</td>
<td>( f(97.6424) = 8.2230 )</td>
</tr>
<tr>
<td>2</td>
<td>3.7897</td>
<td>( f(101.2103) = 3.9882 )</td>
</tr>
<tr>
<td>3</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>4</td>
<td>8.5589</td>
<td>( f(96.4411) = 9.3329 )</td>
</tr>
<tr>
<td>5</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>6</td>
<td>9.1625</td>
<td>( f(95.8375) = 9.83042 )</td>
</tr>
<tr>
<td>7</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>8</td>
<td>0.8525</td>
<td>( f(104.1475) = -0.551885 )</td>
</tr>
</tbody>
</table>
A Numerical Example (continued)

- The put should be exercised for 1 path only: 8.
  - Note that $f(104.1475) < 0$.

- Now, any positive future cash flow should be set to zero or overridden for this path.
  - But there is none.

- The cash flows on p. 907 become the ones on next slide.

- They also confirm the plot on p. 898.
A Numerical Example (continued)

Cash flows at years 1, 2, & 3

<table>
<thead>
<tr>
<th>Path</th>
<th>Year 0</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>—</td>
<td>0</td>
<td>12.4185</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>—</td>
<td>0</td>
<td>0</td>
<td>2.5476</td>
</tr>
<tr>
<td>3</td>
<td>—</td>
<td>0</td>
<td>1.3990</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>—</td>
<td>0</td>
<td>6.2880</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>—</td>
<td>0</td>
<td>3.9436</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>—</td>
<td>0</td>
<td>11.2730</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>—</td>
<td>0</td>
<td>2.5823</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>—</td>
<td>0.8525</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
A Numerical Example (continued)

• We move on to year 0.

• The continuation value is, from p 914,

\[
\frac{(12.4185 \times 0.951229^2 + 2.5476 \times 0.951229^3 \\
+ 1.3990 \times 0.951229^2 + 6.2880 \times 0.951229^2 \\
+ 3.9436 \times 0.951229^2 + 11.2730 \times 0.951229^2 \\
+ 2.5823 \times 0.951229^2 + 0.8525 \times 0.951229)}{8} \\
= 4.66263.
\]
A Numerical Example (concluded)

- As this is larger than the immediate exercise value of $105 - 101 = 4$,

  the put should not be exercised at year 0.

- Hence the put’s value is estimated to be 4.66263.

- Compare this with the European put’s value of 1.3680 (p. 900).
Time Series Analysis
The historian is a prophet in reverse.
— Friedrich von Schlegel (1772–1829)
GARCH Option Pricing\textsuperscript{a}

- Options can be priced when the underlying asset’s return follows a GARCH process.
- Let $S_t$ denote the asset price at date $t$.
- Let $h_t^2$ be the conditional variance of the return over the period $[t, t + 1]$ given the information at date $t$.
  - “One day” is merely a convenient term for any elapsed time $\Delta t$.

\textsuperscript{a}ARCH (autoregressive conditional heteroskedastic) is due to Engle (1982), co-winner of the 2003 Nobel Prize in Economic Sciences. GARCH (generalized ARCH) is due to Bollerslev (1986) and Taylor (1986). A Bloomberg quant said to me on Feb 29, 2008, that GARCH is seldom used in trading.
GARCH Option Pricing (continued)

- Adopt the following risk-neutral process for the price dynamics:\(^{a}\)

\[
\ln \frac{S_{t+1}}{S_t} = r - \frac{h_t^2}{2} + h_t \epsilon_{t+1},
\]

(120)

where

\[
h_{t+1}^2 = \beta_0 + \beta_1 h_t^2 + \beta_2 h_t^2 (\epsilon_{t+1} - c)^2,
\]

(121)

\[
\epsilon_{t+1} \sim N(0, 1) \text{ given information at date } t,
\]

\[
r = \text{ daily riskless return},
\]

\[
c \geq 0.
\]

\(^{a}\)Duan (1995).
GARCH Option Pricing (continued)

- The five unknown parameters of the model are $c$, $h_0$, $\beta_0$, $\beta_1$, and $\beta_2$.
- It is postulated that $\beta_0, \beta_1, \beta_2 \geq 0$ to make the conditional variance positive.
- There are other inequalities to satisfy (see text).
- The above process is called the nonlinear asymmetric GARCH (or NGARCH) model.
GARCH Option Pricing (continued)

- It captures the volatility clustering in asset returns first noted by Mandelbrot (1963).\(^a\)
  
  - When \( c = 0 \), a large \( \epsilon_{t+1} \) results in a large \( h_{t+1} \), which in turns tends to yield a large \( h_{t+2} \), and so on.

- It also captures the negative correlation between the asset return and changes in its (conditional) volatility.\(^b\)
  
  - For \( c > 0 \), a positive \( \epsilon_{t+1} \) (good news) tends to decrease \( h_{t+1} \), whereas a negative \( \epsilon_{t+1} \) (bad news) tends to do the opposite.

\(^a\)“... large changes tend to be followed by large changes—of either sign—and small changes tend to be followed by small changes ...”

\(^b\)Noted by Black (1976): Volatility tends to rise in response to “bad news” and fall in response to “good news.”
GARCH Option Pricing (concluded)

- With $y_t \triangleq \ln S_t$ denoting the logarithmic price, the model becomes

$$y_{t+1} = y_t + r - \frac{h_t^2}{2} + h_t \epsilon_{t+1}. \quad (122)$$

- The pair $(y_t, h_t^2)$ completely describes the current state.

- The conditional mean and variance of $y_{t+1}$ are clearly

$$E[y_{t+1} \mid y_t, h_t^2] = y_t + r - \frac{h_t^2}{2}, \quad (123)$$

$$\text{Var}[y_{t+1} \mid y_t, h_t^2] = h_t^2. \quad (124)$$
GARCH Model: Inferences

• Suppose the parameters $c$, $h_0$, $\beta_0$, $\beta_1$, and $\beta_2$ are given.

• Then we can recover $h_1, h_2, \ldots, h_n$ and $\epsilon_1, \epsilon_2, \ldots, \epsilon_n$ from the prices

  $$S_0, S_1, \ldots, S_n$$

  under the GARCH model (120) on p. 920.

• This property is useful in statistical inferences.
The Ritchken-Trevor (RT) Algorithm\textsuperscript{a}

- The GARCH model is a continuous-state model.
- To approximate it, we turn to trees with \textit{discrete} states.
- Path dependence in GARCH makes the tree for asset prices explode exponentially (why?).
- We need to mitigate this combinatorial explosion.

\textsuperscript{a}Ritchken & Trevor (1999).
The RT Algorithm (continued)

- Partition a day into \( n \) periods.
- Three states follow each state \((y_t, h_t^2)\) after a period.
- As the trinomial model combines, each state at date \( t \) is followed by \( 2n + 1 \) states at date \( t + 1 \) (recall p. 712).
- These \( 2n + 1 \) values must approximate the distribution of \((y_{t+1}, h_{t+1}^2)\).
- So the conditional moments (123)–(124) at date \( t + 1 \) on p. 923 must be matched by the trinomial model to guarantee convergence to the continuous-state model.
The RT Algorithm (continued)

- It remains to pick the jump size and the three branching probabilities.

- The role of $\sigma$ in the Black-Scholes option pricing model is played by $h_t$ in the GARCH model.

- As a jump size proportional to $\sigma/\sqrt{n}$ is picked in the BOPM, a comparable magnitude will be chosen here.

- Define $\gamma \Delta h_0$, though other multiples of $h_0$ are possible, and

$$\gamma_n \triangleq \frac{\gamma}{\sqrt{n}}.$$
The RT Algorithm (continued)

- The jump size will be some integer multiple $\eta$ of $\gamma_n$.
- We call $\eta$ the jump parameter (see next page).
- Obviously, the magnitude of $\eta$ grows with $h_t$.
- The middle branch does not change the underlying asset’s price.
The seven values on the right approximate the distribution of logarithmic price $y_{t+1}$. 
The RT Algorithm (continued)

- The probabilities for the up, middle, and down branches are

\[
    p_u = \frac{h_t^2}{2\eta^2\gamma^2} + \frac{r - (h_t^2/2)}{2\eta\gamma\sqrt{n}}, \quad (125)
\]

\[
    p_m = 1 - \frac{h_t^2}{\eta^2\gamma^2}, \quad (126)
\]

\[
    p_d = \frac{h_t^2}{2\eta^2\gamma^2} - \frac{r - (h_t^2/2)}{2\eta\gamma\sqrt{n}}. \quad (127)
\]
The RT Algorithm (continued)

• It can be shown that:
  – The trinomial model takes on $2n + 1$ values at date $t + 1$ for $y_{t+1}$.
  – These values have a matching mean for $y_{t+1}$.
  – These values have an asymptotically matching variance for $y_{t+1}$.

• The central limit theorem guarantees convergence as $n$ increases.$^a$

---

$^a$Assume the probabilities are valid.
The RT Algorithm (continued)

• We can dispense with the intermediate nodes *between* dates to create a \((2n + 1)\)-nomial tree (p. 933).

• The resulting model is multinomial with \(2n + 1\) branches from any state \((y_t, h_t^2)\).

• There are two reasons behind this manipulation.
  – Interdate nodes are created merely to approximate the continuous-state model after one day.
  – Keeping the interdate nodes results in a tree that can be \(n\) times larger.\(^a\)

\(^a\)Contrast it with the case on p. 396.
This heptanomial tree is the outcome of the trinomial tree on p. 929 after its intermediate nodes are removed.
The RT Algorithm (continued)

• A node with logarithmic price $y_t + \ell \eta \gamma_n$ at date $t + 1$ follows the current node at date $t$ with price $y_t$, where

$$-n \leq \ell \leq n.$$ 

• To reach that price in $n$ periods, the number of up moves must exceed that of down moves by exactly $\ell$.

• The probability that this happens is

$$P(\ell) \triangleq \sum_{j_u, j_m, j_d} \frac{n!}{j_u! j_m! j_d!} p_u^{j_u} p_m^{j_m} p_d^{j_d},$$

with $j_u, j_m, j_d \geq 0$, $n = j_u + j_m + j_d$, and $\ell = j_u - j_d$. 
The RT Algorithm (continued)

- A particularly simple way to calculate the $P(\ell)$s starts by noting that

$$ (p_u x + p_m + p_d x^{-1})^n = \sum_{\ell=-n}^{n} P(\ell) x^\ell. $$  \hspace{1cm} (128)

- Convince yourself that this trick does the “accounting” correctly.

- So we expand $(p_u x + p_m + p_d x^{-1})^n$ and retrieve the probabilities by reading off the coefficients.

- It can be computed in $O(n^2)$ time, if not less.
The RT Algorithm (continued)

- The updating rule (121) on p. 920 must be modified to account for the adoption of the discrete-state model.

- The logarithmic price $y_t + \ell \eta \gamma_n$ at date $t + 1$ following state $(y_t, h_t^2)$ is associated with this variance:

$$h_{t+1}^2 = \beta_0 + \beta_1 h_t^2 + \beta_2 h_t^2 (\epsilon'_{t+1} - c)^2,$$

(129)

- Above,

$$\epsilon'_{t+1} = \frac{\ell \eta \gamma_n - (r - h_t^2/2)}{h_t}, \quad \ell = 0, \pm 1, \pm 2, \ldots, \pm n,$$

is a discrete random variable with $2n + 1$ values.
The RT Algorithm (continued)

- Different conditional variances $h_t^2$ may require different $\eta$ so that the probabilities calculated by Eqs. (125)–(127) on p. 930 lie between 0 and 1.
- This implies varying jump sizes.
- The necessary requirement $p_m \geq 0$ implies $\eta \geq h_t/\gamma$.
- Hence we try
  \[ \eta = \lceil h_t/\gamma \rceil, \lceil h_t/\gamma \rceil + 1, \lceil h_t/\gamma \rceil + 2, \ldots \]
  until valid probabilities are obtained or until their nonexistence is confirmed.
The RT Algorithm (continued)

- The sufficient and necessary condition for valid probabilities to exist is\(^a\)

\[
\frac{|r - (h_t^2/2)|}{2\eta\gamma\sqrt{n}} \leq \frac{h_t^2}{2\eta^2\gamma^2} \leq \min \left(1 - \frac{|r - (h_t^2/2)|}{2\eta\gamma\sqrt{n}}, \frac{1}{2}\right).
\]

- The plot on p. 939 uses \(n = 1\) to illustrate our points for a 3-day model.

- For example, node \((1, 1)\) of date 1 and node \((2, 3)\) of date 2 pick \(\eta = 2\).

\(^a\)C. Wu (R90723065) (2003); Lyuu & C. Wu (R90723065) (2003, 2005).
\( \gamma_n = \gamma_1 \)
The RT Algorithm (continued)

- The topology of the tree is not a standard combining multinomial tree.

- For example, a few nodes on p. 939 such as nodes $(2, 0)$ and $(2, -1)$ have *multiple* jump sizes.

- The reason is path dependency of the model.
  - Two paths can reach node $(2, 0)$ from the root node, each with a different variance for the node.
  - One variance results in $\eta = 1$.
  - The other results in $\eta = 2$. 
The RT Algorithm (concluded)

• The number of possible values of $h_t^2$ at a node can be exponential.
  – Because each path brings a different variance $h_t^2$.

• To address this problem, we record only the maximum and minimum $h_t^2$ at each node.\(^a\)

• Therefore, each node on the tree contains only two states $(y_t, h_{\text{max}}^2)$ and $(y_t, h_{\text{min}}^2)$.

• Each of $(y_t, h_{\text{max}}^2)$ and $(y_t, h_{\text{min}}^2)$ carries its own $\eta$ and set of $2n + 1$ branching probabilities.

\(^a\)Cakici & Topyan (2000). But see p. 976 for a potential problem.
Negative Aspects of the Ritchken-Trevor Algorithm\textsuperscript{a}

- A small \( n \) may yield inaccurate option prices.
- But the tree will grow exponentially if \( n \) is large enough.
  - Specifically, \( n > (1 - \beta_1)/\beta_2 \) when \( r = c = 0 \).
- A large \( n \) has another serious problem: The tree cannot grow beyond a certain date.
- Thus the choice of \( n \) may be quite limited in practice.
- The RT algorithm can be modified to be free of shortened maturity and exponential complexity.\textsuperscript{b}

\textsuperscript{a}Lyuu & C. Wu (R90723065) (2003, 2005).
\textsuperscript{b}Its size is only \( O(n^2) \) if \( n \leq (\sqrt{(1 - \beta_1)/\beta_2 - c})^2 \)!
Numerical Examples

- Assume
  - \( S_0 = 100, \ y_0 = \ln S_0 = 4.60517 \).
  - \( r = 0 \).
  - \( n = 1 \).
  - \( h_0^2 = 0.0001096, \ \gamma = h_0 = 0.010469 \).
  - \( \gamma_n = \gamma/\sqrt{n} = 0.010469 \).
  - \( \beta_0 = 0.000006575, \ \beta_1 = 0.9, \ \beta_2 = 0.04, \) and \( c = 0 \).
Numerical Examples (continued)

• A daily variance of 0.0001096 corresponds to an annual volatility of

\[ \sqrt{365 \times 0.0001096} \approx 20\%. \]

• Let \( h^2(i, j) \) denote the variance at node \( (i, j) \).

• Initially, \( h^2(0, 0) = h_0^2 = 0.0001096 \).
Numerical Examples (continued)

• Let $h_{\text{max}}^2(i, j)$ denote the maximum variance at node $(i, j)$.

• Let $h_{\text{min}}^2(i, j)$ denote the minimum variance at node $(i, j)$.

• Initially, $h_{\text{max}}^2(0, 0) = h_{\text{min}}^2(0, 0) = h_0^2$.

• The resulting 3-day tree is depicted on p. 946.
• A top number inside a gray box refers to the minimum variance $h^2_{\text{min}}$ for the node.

• A bottom number inside a gray box refers to the maximum variance $h^2_{\text{max}}$ for the node.

• Variances are multiplied by 100,000 for readability.

• The top number inside a white box refers to the $\eta$ for $h^2_{\text{min}}$.

• The bottom number inside a white box refers to the $\eta$ for $h^2_{\text{max}}$. 
Numerical Examples (continued)

• Let us see how the numbers are calculated.

• Start with the root node, node \((0, 0)\).

• Try \(\eta = 1\) in Eqs. (125)–(127) on p. 930 first to obtain

\[
\begin{align*}
p_u & = 0.4974, \\
p_m & = 0, \\
p_d & = 0.5026.
\end{align*}
\]

• As they are valid probabilities, the three branches from the root node use single jumps.
Numerical Examples (continued)

- Move on to node (1, 1).
- It has one predecessor node—node (0, 0)—and it takes an up move to reach the current node.
- So apply updating rule (129) on p. 936 with $\ell = 1$ and $h_t^2 = h^2(0, 0)$.
- The result is $h^2(1, 1) = 0.000109645$. 
Numerical Examples (continued)

• Because $\lceil h(1, 1)/\gamma \rceil = 2$, we try $\eta = 2$ in Eqs. (125)–(127) on p. 930 first to obtain

\[
\begin{align*}
 p_u &= 0.1237, \\
 p_m &= 0.7499, \\
 p_d &= 0.1264.
\end{align*}
\]

• As they are valid probabilities, the three branches from node $(1, 1)$ use double jumps.
Numerical Examples (continued)

• Carry out similar calculations for node \((1,0)\) with \(\ell = 0\) in updating rule (129) on p. 936.

• Carry out similar calculations for node \((1,-1)\) with \(\ell = -1\) in updating rule (129).

• Single jump \(\eta = 1\) works for both nodes.

• The resulting variances are

\[
\begin{align*}
  h^2(1,0) &= 0.000105215, \\
  h^2(1,-1) &= 0.000109553.
\end{align*}
\]
Numerical Examples (continued)

- Node (2, 0) has 2 predecessor nodes, (1, 0) and (1, −1).
- Both have to be considered in deriving the variances.
- Let us start with node (1, 0).
- Because it takes a middle move to reach the current node, we apply updating rule (129) on p. 936 with $\ell = 0$ and $h_t^2 = h^2(1, 0)$.
- The result is $h_{t+1}^2 = 0.000101269$. 
Numerical Examples (continued)

• Now move on to the other predecessor node \((1, -1)\).

• Because it takes an up move to reach the current node, apply updating rule (129) on p. 936 with \(\ell = 1\) and \(h_t^2 = h^2(1, -1)\).

• The result is \(h_{t+1}^2 = 0.000109603\).

• We hence record
  \[
  h_{\text{min}}^2(2, 0) = 0.000101269, \\
  h_{\text{max}}^2(2, 0) = 0.000109603.
  \]
Numerical Examples (continued)

• Consider state \( h_{\text{max}}^2(2, 0) \) first.

• Because \( \lceil h_{\text{max}}(2, 0)/\gamma \rceil = 2 \), we first try \( \eta = 2 \) in Eqs. (125)–(127) on p. 930 to obtain

\[
\begin{align*}
    p_u &= 0.1237, \\
    p_m &= 0.7500, \\
    p_d &= 0.1263.
\end{align*}
\]

• As they are valid probabilities, the three branches from node \((2, 0)\) with the maximum variance use double jumps.
Numerical Examples (continued)

• Now consider state \( h_{\text{min}}^2(2, 0) \).

• Because \( \lceil h_{\text{min}}(2, 0)/\gamma \rceil = 1 \), we first try \( \eta = 1 \) in Eqs. (125)–(127) on p. 930 to obtain

\[
\begin{align*}
p_u &= 0.4596, \\
p_m &= 0.0760, \\
p_d &= 0.4644.
\end{align*}
\]

• As they are valid probabilities, the three branches from node \((2, 0)\) with the minimum variance use single jumps.
Numerical Examples (continued)

• Node \((2, -1)\) has 3 predecessor nodes.

• Start with node \((1, 1)\).

• Because it takes one down move to reach the current node, we apply updating rule (129) on p. 936 with \(\ell = -1\) and \(h^2_t = h^2(1, 1)\).\(^a\)

• The result is \(h^2_{t+1} = 0.0001227\).

\(^a\)Note that it is not \(\ell = -2\). The reason is that \(h(1, 1)\) has \(\eta = 2\) (p. 950).
Numerical Examples (continued)

- Now move on to predecessor node \((1, 0)\).
- Because it also takes a down move to reach the current node, we apply updating rule (129) on p. 936 with \(\ell = -1\) and \(h_t^2 = h^2(1, 0)\).
- The result is \(h_{t+1}^2 = 0.000105609\).
Numerical Examples (continued)

• Finally, consider predecessor node $(1, -1)$.

• Because it takes a middle move to reach the current node, we apply updating rule (129) on p. 936 with $\ell = 0$ and $h^2_t = h^2(1, -1)$.

• The result is $h^2_{t+1} = 0.000105173$.

• We hence record

$$h^2_{\min}(2, -1) = 0.000105173, \quad h^2_{\max}(2, -1) = 0.0001227.$$
Numerical Examples (continued)

- Consider state $h_{\text{max}}^2(2, -1)$.
- Because $\lceil h_{\text{max}}(2, -1)/\gamma \rceil = 2$, we first try $\eta = 2$ in Eqs. (125)--(127) on p. 930 to obtain
  
  \[
  p_u = 0.1385, \quad p_m = 0.7201, \quad p_d = 0.1414.
  \]
- As they are valid probabilities, the three branches from node $(2, -1)$ with the maximum variance use double jumps.
Numerical Examples (continued)

• Next, consider state $h_{\text{min}}^2(2, -1)$.

• Because $\lceil h_{\text{min}}(2, -1)/\gamma \rceil = 1$, we first try $\eta = 1$ in Eqs. (125)–(127) on p. 930 to obtain

$$
\begin{align*}
p_u &= 0.4773, \\
p_m &= 0.0404, \\
p_d &= 0.4823.
\end{align*}
$$

• As they are valid probabilities, the three branches from node $(2, -1)$ with the minimum variance use single jumps.
Numerical Examples (concluded)

- Other nodes at dates 2 and 3 can be handled similarly.

- In general, if a node has $k$ predecessor nodes, then up to $2^k$ variances will be calculated using the updating rule.
  - This is because each predecessor node keeps two variance numbers.

- But only the maximum and minimum variances will be kept.
Negative Aspects of the RT Algorithm Revisited\textsuperscript{a}

- Recall the problems mentioned on p. 942.
- In our case, combinatorial explosion occurs when
  \[
  n > \frac{1 - \beta_1}{\beta_2} = \frac{1 - 0.9}{0.04} = 2.5
  \]
  (see the next plot).
- Suppose we are willing to accept the exponential running time and pick \( n = 100 \) to seek accuracy.
- But the problem of shortened maturity forces the tree to stop at date 9!

\textsuperscript{a} Lyuu & C. Wu (R90723065) (2003, 2005).
Dotted line: \( n = 3 \); dashed line: \( n = 4 \); solid line: \( n = 5 \).
Backward Induction on the RT Tree

• After the RT tree is constructed, it can be used to price options by backward induction.

• Recall that each node keeps two variances $h_{\text{max}}^2$ and $h_{\text{min}}^2$.

• We now increase that number to $K$ equally spaced variances between $h_{\text{max}}^2$ and $h_{\text{min}}^2$ at each node.

• Besides the minimum and maximum variances, the other $K - 2$ variances in between are linearly interpolated.\(^a\)

\(^a\)In practice, log-linear interpolation works better (Lyuu & C. Wu (R90723065), 2005). Log-cubic interpolation works even better (C. Liu (R92922123), 2005).
Backward Induction on the RT Tree (continued)

• For example, if $K = 3$, then a variance of

\[10.5436 \times 10^{-6}\]

will be added between the maximum and minimum variances at node $(2,0)$ on p. 946.\(^a\)

• In general, the $k$th variance at node $(i,j)$ is

\[h_{\text{min}}^2(i,j) + k \frac{h_{\text{max}}^2(i,j) - h_{\text{min}}^2(i,j)}{K - 1}, \quad k = 0, 1, \ldots, K-1.\]

• Each interpolated variance’s jump parameter and branching probabilities can be computed as before.

\(^a\)Repeated on p. 966.
Backward Induction on the RT Tree (concluded)

- Suppose a variance falls between two of the $K$ variances during backward induction.

- Linear interpolation of the option prices corresponding to the two bracketing variances will be used as the approximate option price.

- The above ideas are reminiscent of the ones on p. 436, where we dealt with Asian options.
Numerical Examples

• We next use the tree on p. 966 to price a European call option with a strike price of 100 and expiring at date 3.

• Recall that the riskless interest rate is zero.

• Assume $K = 2$; hence there are no interpolated variances.

• The pricing tree is shown on p. 969 with a call price of 0.66346.
  – The branching probabilities needed in backward induction can be found on p. 970.
Numerical Examples (continued)

• Let us derive some of the numbers on p. 969.

• A gray line means the updated variance falls strictly between $h_{\text{max}}^2$ and $h_{\text{min}}^2$.

• The option price for a terminal node at date 3 equals $\max(S_3 - 100, 0)$, independent of the variance level.

• Now move on to nodes at date 2.

• The option price at node (2, 3) depends on those at nodes (3, 5), (3, 3), and (3, 1).

• It therefore equals

$$0.1387 \times 5.37392 + 0.7197 \times 3.19054 + 0.1416 \times 1.05240 = 3.19054.$$
Numerical Examples (continued)

- Option prices for other nodes at date 2 can be computed similarly.
- For node \((1, 1)\), the option price for both variances is
  \[
  0.1237 \times 3.19054 + 0.7499 \times 1.05240 + 0.1264 \times 0.14573 = 1.20241.
  \]
- Node \((1, 0)\) is most interesting.
- We knew that a down move from it gives a variance of \(0.000105609\).
- This number falls between the minimum variance \(0.000105173\) and the maximum variance \(0.0001227\) at node \((2, -1)\) on p. 970.
Numerical Examples (continued)

- The option price corresponding to the minimum variance is 0 (p. 970).
- The option price corresponding to the maximum variance is 0.14573.
- The equation
  \[ x \times 0.000105173 + (1 - x) \times 0.0001227 = 0.000105609 \]
  is satisfied by \( x = 0.9751 \).
- So the option for the down state is approximated by
  \[ x \times 0 + (1 - x) \times 0.14573 = 0.00362. \]
Numerical Examples (continued)

• The up move leads to the state with option price 1.05240.

• The middle move leads to the state with option price 0.48366.

• The option price at node (1, 0) is finally calculated as

$$0.4775 \times 1.05240 + 0.0400 \times 0.48366 + 0.4825 \times 0.00362 = 0.52360.$$
Numerical Examples (continued)

- A variance following an interpolated variance may exceed the maximum variance or be exceeded by the minimum variance.

- When this happens, the option price corresponding to the maximum or minimum variance will be used during backward induction.\(^a\)

\(^a\)Cakici & Topyan (2000).
Numerical Examples (concluded)

• But an interpolated variance may choose a branch that goes into a node that is *not* reached in forward induction.\textsuperscript{a}

• In this case, the algorithm fails.

• The RT algorithm does not have this problem.
  – This is because all interpolated variances are involved in the forward-induction phase.

• It may be hard to calculate the implied $\beta_1$ and $\beta_2$ from option prices.\textsuperscript{b}

\textsuperscript{a}Lyuu & C. Wu (R90723065) (2005).
\textsuperscript{b}Y. Chang (B89704039, R93922034) (2006).
Complexities of GARCH Models\(^a\)

- The RT algorithm explodes exponentially if \( n \) is big enough (p. 942).
- The mean-tracking tree of Lyuu and Wu (2005) makes sure explosion does not happen if \( n \) is not too large.\(^b\)
- The next page summarizes the situations for many GARCH option pricing models.
  - Our earlier treatment is for NGARCH only.

\(^a\)Lyuu & C. Wu (R90723065) (2003, 2005).
\(^b\)Similar to, but earlier than, the binomial-trinomial tree on pp. 735ff.
### Complexities of GARCH Models (concluded)\(^a\)

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<th>Model</th>
<th>Explosion</th>
<th>Non-explosion</th>
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<td>NGARCH</td>
<td>(\beta_1 + \beta_2 n &gt; 1)</td>
<td>(\beta_1 + \beta_2 (\sqrt{n} + \lambda + c)^2 \leq 1)</td>
</tr>
<tr>
<td>LGARCH</td>
<td>(\beta_1 + \beta_2 n &gt; 1)</td>
<td>(\beta_1 + \beta_2 (\sqrt{n} + \lambda)^2 \leq 1)</td>
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<tr>
<td>AGARCH</td>
<td>(\beta_1 + \beta_2 n &gt; 1)</td>
<td>(\beta_1 + \beta_2 (\sqrt{n} + \lambda)^2 \leq 1)</td>
</tr>
<tr>
<td>GJR-GARCH</td>
<td>(\beta_1 + \beta_2 n &gt; 1)</td>
<td>(\beta_1 + (\beta_2 + \beta_3)(\sqrt{n} + \lambda)^2 \leq 1)</td>
</tr>
<tr>
<td>TS-GARCH</td>
<td>(\beta_1 + \beta_2 \sqrt{n} &gt; 1)</td>
<td>(\beta_1 + \beta_2 (\lambda + \sqrt{n}) \leq 1)</td>
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<tr>
<td>TGARCH</td>
<td>(\beta_1 + \beta_2 \sqrt{n} &gt; 1)</td>
<td>(\beta_1 + (\beta_2 + \beta_3)(\lambda + \sqrt{n}) \leq 1)</td>
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<tr>
<td>Heston-Nandi</td>
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<td>(\beta_1 + \beta_2 c^2 \leq 1)</td>
</tr>
<tr>
<td>VGARCH</td>
<td>(\beta_1 + (\beta_2/4) &gt; 1)</td>
<td>(\beta_1 \leq 1)</td>
</tr>
</tbody>
</table>

\(^a\)Y. C. Chen (R95723051) (2008); Y. C. Chen (R95723051), Lyuu, & Wen (D94922003) (2012).